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# Effective Solid Waste Management: A Review of Optimization Techniques

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**ABSTRACT:** Solid wastes and its disposal have been a primary issue in all GCC countries as its effects directly related tothe environment, the health of the peoples, and thus in the economics of the countries. So, the Waste management system and its social and environmental issues becomethe mainstream in many regions of the Sultanate of Oman because of its significance and complexity. Many researches are carried out for an efficient management system. A literature survey shows that collection of wastages is a tedious and cumbersome task. It needs more labor and capital costs. It occupies almost 60% of the total cost of the waste management system.The main aim of this paper is to analyze different optimization techniques that are all used to locate and collect the wastages from the waste bins and to dump it in the dump yards. Several strategies are considered for the analysis to minimize the cost of waste collection and disposal such as transportation, logistic routes, operation, and disposal.

**KEY WARDS: Waste management system, Optimization techniques, Logistic routes**

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## I. INTRODUCTION

Solid waste management is a challenging task in the Sultanate of Oman because of its limited land availability. The growing population also worsening the situation as its population nearing 4.5 billion. It is estimated that yearly, Oman generates approximately 1.7 million tonsof solid waste that is equivalent to 0.97 Kg/day/person [1]. According to the survey conducted in 2013, 18% of the solid waste was occupied by paper wastes, 27% by plastics, glass, and metals by 6% and food 14 % [2]. .most of these wastagesare dumped in authorized or unauthorized dump yards, which creates serious environmental issues.Some of the recent studies show that some of the dump yards are located very near to the private and public drinking water bodies.

A recent survey shows that solid waste management is very poor in Oman by the lack of collection and disposal facilities. Poor sanitary and technically inefficient waste management system is considered as a challenging task for researchers to overcome this issue. Inadequate transportations and lack of public cooperation are the main causes of poor waste management in developing countries like Oman. Collection, storage, processing, and landfilling of wastages needs, controlled regulation, and continuous monitoring. While implementing this process, it is necessary to consider the health principles guided by government authorities, economy, and natural resources [3]-[4]. Oman facing problems in these issues, so, it needs high-endpractical solutions. Currently, many research works are carried outon integrated Solid waste management systems [5].

Waste collection in a small area with less number of collection nodes is easy. However, large collection area with more collection points, increase the complexity of management where the role of decision-making systems become necessary [6].During this decision-making process, some parameters (Execution time, number of iterations, etc…) needed to be maintained within the limit. Someintelligent systems and optimization techniques had proven as efficient ones to get the optimal solution for theseparameters. Usually, good decision-makingis obtainedby case studies, trial and errors,andcomparison of possible solutionsof the different waste management systems. [7].

Recent surveys show that optimization techniques play a major role in the decision-making process especially for optimizing the waste collection routes. This paper intended to analyze different optimization techniques which are all utilized to select optimal routes for the waste-collecting trucks from waste collection nodes or points to the dump yards.

In Oman, the increasing population, commercial complexes, and residential apartments have resulted ina large accumulation of solid wastes like residential (Biodegradable), industrial, and e-wastes (Non-biodegradable) materials. Survey results show that over 80% of the solid wastes are recycled in developed nations like the USA and UK.

## II. RELATED WORKS

Recently, many theoretical and practical research works are carried out onurban solid waste management system to improve its efficiency.The practical research works focused on complete automation in solid waste management and planning.On the other hand, theoretical works focused on socio-economic issues like a conflict between the residents and municipal authorities, for site selections(for dump yards, waste treatment, and recycling plants and waste collection and transportation costs. [8]-[10].

In the literature survey, many research works are focused on the optimal routing of solid waste networks as it cost 40% of the total cost of the waste management system. Optimal route selection and scheduling the waste collection trucks are considered as primary factors in theseworks. A random collection of wastes and trial and error methods are provedas inefficient in these works.So, to improve the overall efficiency of the waste collection system, many mathematical programming methods are developed by researchers. [11]-[12].

Some methods focused on minimizing the total distance between the waste-collecting bins to the dumpyard and some methods are focused on reducing the number of trucks utilized for waste collection purposes.Many optimizing techniques are proposed for these approaches like traveling salesman problem, Chinese postman problem, genetic algorithm, ant colony optimization algorithm, particle swarm optimization and bee colony algorithm, branch and border algorithm, branch, and cutoff algorithm.

The formulation of these programming models for waste management systems needswaste bins locations, road network data, and population density. All these requirements are satisfied by using a geographic information system(GIS). GIS facilitates the conducive environment for these programming models toimprove effective waste management system [13]-[15].

### 2.1.Waste management system by Ant Colony Optimization

In this approach, a set of loading spots of the garbage collecting trucks are assumed as a nodes $X_n(i,j)$ of the network. Then, the distance between the nodes$W_n$is considered as a link parameter between the nodes. The $W_n$is calculated by

$$W_n = \{\left(X_{n+1}(i) - X_n(i)\right)^2 - \left(X_{n+1}(j) - X_n(j)\right)^2\}^{\frac{1}{2}} \qquad (1)$$

Where i,j = 0,1,2,3,…n, x =1,2,3,…..m.

Then, the set of artificial ants$k_m$is assumed to visit all the nodes randomly with the condition that each ant visits nodes only once on a trip.

Initially, artificial ants are trained to visit closer nodes to form a mesh. Once, the complete network is covered in this aspect. The pheromone (P) is deposited in each link of the network under the assumption that its concentration (visibility) in the node is inversely proportional to the distance between the nodes.

$$V_{(i,j)} = \frac{1}{W_{(i,j)}} \qquad (2)$$

Here, $V_{(i,j)}$ represents the trail of visibility between the nodes and

$d_{(i,j)}$represents the distance between the nodes.

So, sorter distance receives more pheromone trails and longer distance receives lesser pheromone trails.Again, the artificial ants are made to visit the nodes, but, this time, the ants select the routes based on the pheromone deposition. The probability of selecting nodes is given by

$$p(t)^k_{(i,j)} = \frac{[I(t)^a_{(i,j)}][V(t)^b_{(i,j)}]}{\Sigma\ [I(t)^a_{(i,j)}][V(t)^b_{(i,j)}]} \qquad (3)$$

Here p represents the probability of k ants selecting the nodes, I(t) represents the intensity of trail, V(t) represents the visibility of trail and ‘a’ and ‘b’ represents the coefficients of the intensity and visibility respectively.

Mostly, all the ants are programmed to select the link which has high pheromone deposition. The pheromone factors are programmed to evaporate at a constant rate.

So, automatically the nodes and links with less pheromone are favor, less attraction to the ants, and the other end, high concentrated pheromone nodes, and links are repeatedly used by ants and thus have more concentration of pheromones. Finally, the artificial ants can find the optimal routes from waste bins to the dump yards.

But, this method has drawbacks too, like, sometimes the artificial ants ended with more than one shortest route as these ants continuously exploring alternative paths to obtain the dump yards[16]-[18].

This ant colony optimization method is programmed with the following steps with certain constraints.

(i) Initially, artificial ants are placed in the locations of all waste bins.So, the number of dust bins (nodes) is equal to the number of artificial ants.

(ii) Every artificial ants choose its path based on The pheromone trails in the nodes and links.

(iii) Revisiting the waste bins(network nodes) are not allowed until every ant completes its tour. That means to reach the dump yards.

(iv) Once the ant completes its tour. It updates pheromone in nodes and leaves its trails.

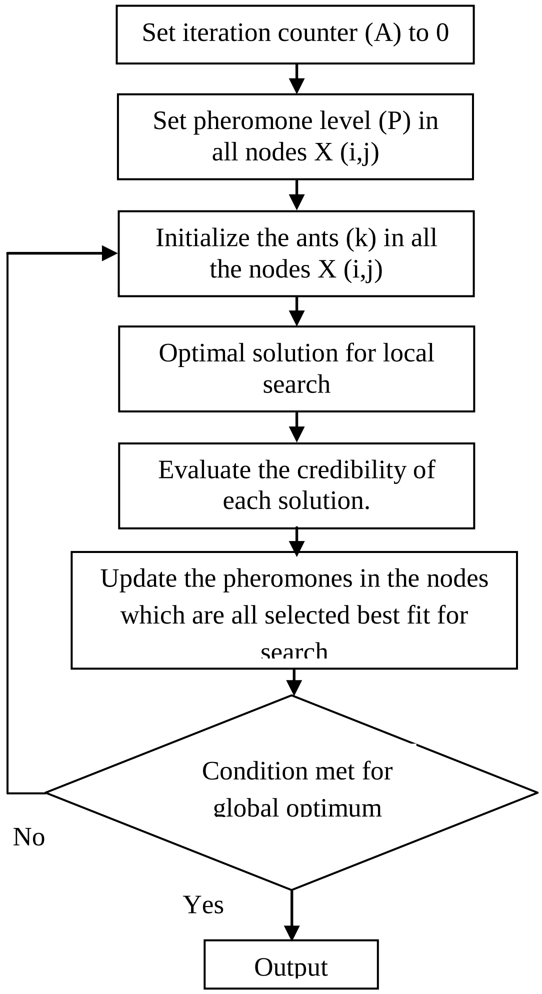



**Figure 1 Flow chart of Ant colony optimization**

The procedures of the ant colony optimization are stated as follows.

Step 1: Set iteration counter (A) to 0

Step 2: Set pheromone level (P) in all nodes X (i,j) (waste bin locations) to its initial value.

Step 3: Initialize the ants (k) in all the nodes X (i,j) with the assumption that the number of ants is equal to the number of nodes.

$X(i,j)_n = f(k_m)|_{n=m}$ .............................................................................................(4)

Where n and m represent the number of ants and nodes respectively.

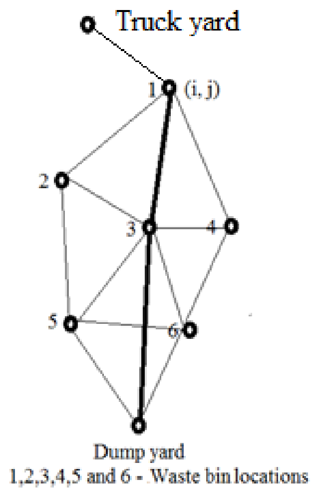



**Figure 2 Waste collection network**

Step 4: Obtain the solution for each ant with the help of three parameters

(a) Probability $(p(t)_{(i,j)}^{k})$ of maximum pheromone $P_{max}$ at the nodes $X_n$(i,j).

(b) Distribution constant.

© Random selection of nodes.

Step 5: Optimal solution for local search.

Step 6: Evaluate the credibility of each solution.

Step 7: Update the pheromones in the nodes which are all selected best fit for search.

$$\Delta \mathrm{I}(\mathrm{t})_{(i,j)}^{a} = \rho \mathrm{I}(\mathrm{t}-1)_{(i,j)}^{a} + \sum_{k=1}^{m} \Delta \mathrm{I}(\mathrm{t})_{(i,j)}^{a} \quad \text{.........................................................(5)}$$

Where $\rho$ represents the evaporation factor which is always bound between 0 to 1 ($0 \leq \rho \leq 1$)[19]-[20].

Step 8: initialize the number of tours for the ants until global optimum obtained for the network.

This method provides a good solution for the networks even they are large in size as the ants randomly discovering the nodes. Also, it provides assured convergence for the problem. But, it has certain limitations too like an uncertain period of convergence.

**2.2 Waste management system by Genetic Algorithm**

The genetic algorithm mimics the natural evaluation process, to obtain an optimal solution for complex mathematical problems. The waste management system is one of the complex areas where GA yields a good solution to estimate the shortest route between waste bins to the dump yard.

The genetic algorithm requires the variables which decide the trial solutions for the string of codes (waste bin locations).

This coded strings($\vec{a}_1, \vec{a}_2$, etc..) resembles the genes in the bio chromosomes. Every nodeof the network is assigned with these decision variables for the trial solutions.

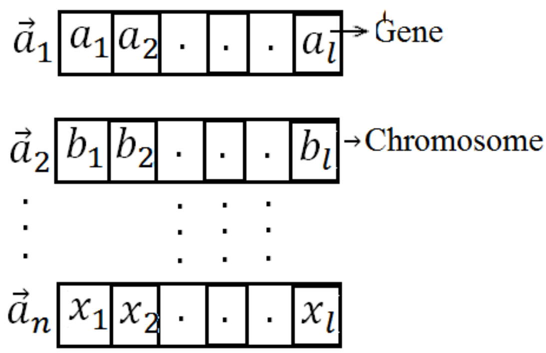



**Figure 3 Gene and chromosome in the population**

Depending on the size of the network, the number of substrings is made to represent the problem with a genetic algorithm [21]-[22]. A string of genes represents the route design for the complete network. The first gene (first waste bin location) has not been made as an initial location. But, the last gene (dump yard) is considered as a destination that means the final node of the network.

**(i) Fitness:**

The fitness of the coded string (chromosome) represents the shortest route provided by the waste-collecting trucks passes through each node (waste bins) once on a trip. Usually, The evaluation function is determined by adding the length of the links (the route between the waste bins).Sometimes, an infeasible solution may attainbecause of the evaluation function.later, these infeasible solutions are added in the population to improve the level of search.For this application, the evaluation function is minimized to obtain the shortest route.

The step by step procedure for the genetic algorithm is given below.

**(ii) Encoding:**

Embedding the coded variables (waste bin locations) in the chromosome.

$\vec{a}_1 = (a_1, a_2, a_3, \dots \dots \dots \dots . a_l)$ ................................................................(6)

$\vec{a}_2 = (b_1, b_2, b_3, \dots \dots \dots \dots . b_l)$ ................................................................(7)

. . . . .

. . . . .

$\vec{a}_n = (x_1, x_2, x_3, \dots \dots \dots \dots . x_l)$ ................................................................(8)

Here $\vec{a}_1, \vec{a}_2 \& \vec{a}_n$ are represents the coded strings.

**(iii) Initial Population:**

Sampling the decision variables randomly within the specific range.

$P(0) = \{\vec{a}_1(0), \vec{a}_2(0), \dots \dots \dots \vec{a}_n(0)\}_{\in l}$ ................................................(9)

Where l represents the length of a chromosome

**(iv) Fitness evaluation:**

Optimizing the model for minimum length with the help of evaluation function.

$P(0) = \left\{\emptyset(\vec{a}(0)), \emptyset(\vec{b}(0)), \dots \dots \dots \emptyset(\vec{n}(0)\right\}_{\in l}$......................................(10)

**(v) Selection:**

Random sampling the pairs of individuals in the roulette wheel. The individuals presenting high fitness value has a larger probability to propagate into the next generation.

$p(\vec{a}_1(t)) = \frac{f(\vec{a}_1(t))}{\sum_{l=1}^{N}(\vec{a}_l(t)}$ ..........................................................................(11)

Where $p(\vec{a}_1(t))$ represents the probability of the individual $\vec{a}_1(t)$ and $f(\vec{a}_1(t))$ represents the fitness function of the individual $\vec{a}_1(t)$

**(vi) Cross over:**

Two selected parents are cross over to produce two children or offsprings. Thiscross overperformed with high probability otherwise children resembles their parents.The child 1 or offspring 1is represented by

$\vec{C}_1 = \gamma_i \vec{a}_1 + (1 - \gamma_i)\vec{a}_2$.....................................................................(12)

$\vec{C}_2 = (1 - \gamma_i)\vec{a}_1 + \gamma_i \vec{a}_2$ ..................................................................(13)

Where $\gamma_i$ represented by

$\gamma_i = (1 + 2a)u_i - a$ ......................................................................... (14)

Where ‘a’ represents the probability which is always higher in value to avoid the resemblance of the offsprings with their parents. The literature survey shows that it is always in the range of 0.5 to 0.6 for better probability [23]-[24].

**(vii) Mutation:**

The mutation produces diversity in the population by occasional replacement of individuals by the probability

$p = \frac{i}{l}$.......................................................................................................(15)

where l represents the length of the string and

i represents the mutation rate.

Finally,the obtained encoded array represents the solution to the problem. In this case. It represents the shortest route between waste bins to the dump yards.

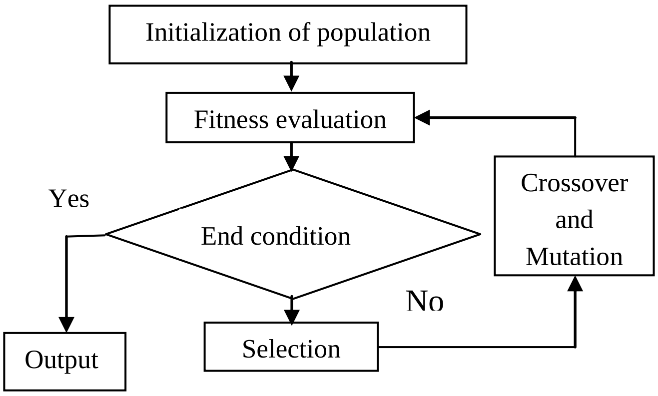



**Figure 4 Genetic Algorithm**

### 2.3 Waste management system by Particle Swarm Optimization

Swarm intelligence shows the behavior of social insects like ants and birds, which is normally used in optimization related problems.Particle swarm optimization is the evolutionary algorithm mimicked from flocks of bird's behavioral patterns while they are in search. This is the widely used optimization technique to resolve both continuous and discrete problems [25]-[26]. The important terms used in this approach is given below.

**(i) Search Phase:**
This is the space where the desired solution is obtained.

**(ii)Population:**
It is formed by the particles.

**(iii) Particle:**

Particle (P) is assumed as a point in the space with position and velocity as its characteristics.
The position is represented by a vector
$x_{i\,j}^{t} = (x_{i\,1}, x_{i\,2}, x_{i\,3}, \dots \dots \dots \dots . x_{i\,l})^{T}$ ..........................................................(16)
And the velocity of the particle is estimated by a vector
$V_{i\,j}^{t} = (V_{i\,1}, V_{i\,2}, V_{i\,3}, \dots \dots \dots \dots . V_{i\,l})^{T}$ ..........................................................(17)
The velocity has both speed and direction. This parameter of the particle moves the whole system into the optimal solution.

The PSO algorithm deals with the population and velocity of the points to drag them towards the best solution.In the beginning, all the particles are assumed with random positions with random velocities in the search phase.

Its velocities in each iteration with the following steps, update the optimized positions of the particles. The optimized solution of the particles is represented by the term fitness.Usually, the fitness of the particle is obtained by tracking its two best positions [27].

The best positions are justified by the fitness and value of the particles. This is called the neighborhood's best. When this level of the neighborhood is best reached for the whole population. Then, the global best solution is obtained.

The step by step procedure of PSO algorithm is gevn below.

**(i) Initial particle:**
The routes to collect waste from waste bins to dump yards are considered as an initial particle.

**(ii) Velocity update:**
The initial velocity of the routes isnormally assigned randomly. Then, based on this, later the velocities are updated based on the particle swarm optimization algorithm.
$V_{i\,j}^{t+1} = aV_{i\,j}^{t} + c_1 r_1^t\left(P_b t_{i\,j} - x_{i\,j}^{t}\right) + c_2 r_2^t\left(G_b t_{i\,j} - x_{i\,j}^{t}\right)$ ......................................(18)
Where i=1,2,….,m and
j=1,2,….,n
Here

'a' represents the inertia weight constant. This constant is essential to balance the global search.it is always bounded between $0 \leq a \leq 1$ [28]-[29].

$c_1$ represents the cognition parameter of the individuals.

$r_1$ and $r_2$represent the random values thatare bounded between 0 to 1.

$P_b$ is the personal best for the solution, it represents the best fitness of the particle.

$G_b$ is the global best for the solution, it represents the best fitness of the population.

The minimum and maximum range of velocities are fixed for this particle to avoid the updated velocities are going beyond its limit.

**(iii) Particle update:**

The new position of the particle is calculated by

$x_{i\,j}^{t+1} = x_{i\,j}^{t} + V_{i\,j}^{t+1}$ ..............................................................................(19)

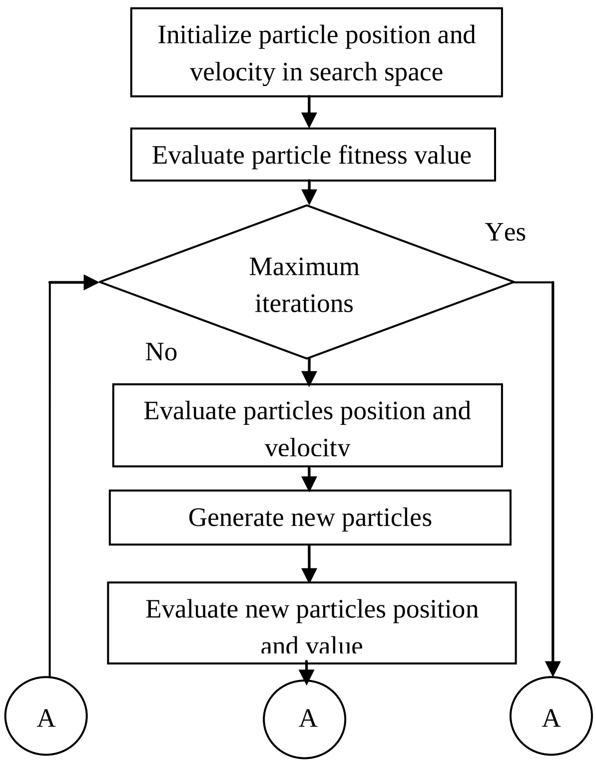
The particle updation carried out between minimum and maximum value ranges.

**(iv) Fitness:**

The path with the least fitness is considered as the best path in the network. Fitness usually represents the total distance covered by the waste-collecting truck from waste bins to the dump yard.

**(v) Route construction:**

After waste collecting trucks visiting the collection points (waste bins), the routes of the truck are updated by decision variables.In this approach, the precision depends upon the number of iterations. More number of iterations yields good result.If, the number of iterations is less. Then, the new particles are produced from the updation of old particles position and velocity [30]-[31]



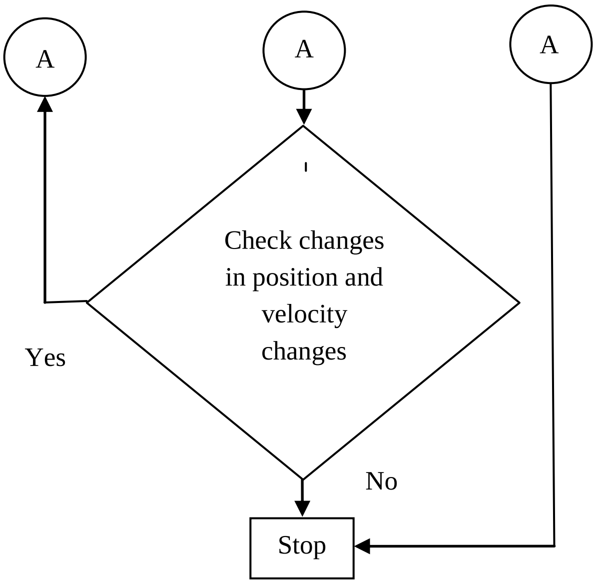



**Figure 5Particle Swarm Optimization**

Then, the new particles were evaluated. If, no considerable changes in the position and velocity, then, the path with the least fitness is considered as the best path.

**2.4 Waste management system by Tabu Search:**

Glover introduced the Tabu search as a metaheuristic algorithm to enhance the performance of another heuristic algorithm. This optimization technique uses a local search to move improved solution from the potential solution until stopping criterion satisfied. The Tabu search explores neighborhood solutions to make progress in the search. During this search, the solution is admitted as a neighborhood solution by checking the Tabu list (memory structure) [32]-[33]

The memory structure used in this search is categorized into:

- Short term - memory with recently considered solutions
- Intermediate-term - memory with solutions in the promising area in the network
- Long term -memory with solutions including new regions of the network.

But, while implementations, these three kinds of memories overlap to met good results at the end. For many problems, short term memory itself enough to obtain a good result as compared to other conventional methods. But, if the problems are harder, then, the intermediate and long term memories are needed [34]-[35].

(i)The initial solution is createdby emptying the Tabu list. In this way, the memory structure was initialized for the solution.The nearest neighborhood heuristic method is used to obtain the initial solution. The node $X_{ij}$ and link distance $d_n$ between the links are considered as parameters.

The $d_x$ is estimated by the formula

$$d_n = \{\left(X_{n+1}(i) - X_n(i)\right)^2 - \left(X_{n+1}(j) - X_n(j)\right)^2\}^{\frac{1}{2}} \quad \text{....................................(20)}$$

Where i,j = 0,1,2,3,…n, x =1,2,3,…..m.

The function which represents the above parameters is represented by

$$F_{ij} = \frac{X_{ij}}{d_n} \quad \text{.......................................................................................................... (21)}$$

(ii)The neighborhood is revealed by the many possibleoperators. They are:

(a) Random operators
(b) Long route operator
(c) Short route improvement operator
(d) Random route improvement operator

(a) Random operators

This operator is used to randomly select one node (waste bin location) by the initial solution.

(b) Long route operator

This operator is used to select the node which has long-distance with the adjacent node.

$$X_n(i,j) = max\begin{Bmatrix} \{\left(X_{n+1}(i) - X_n(i)\right)^2 -^{\frac{1}{2}} \\ \left(X_{n+1}(j) - X_n(j)\right)^2\} \end{Bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (22)$$

(c) Short route improvement operator
This operates is used to delete or combine short distance nodes to make long-distance nodes by reassigning them with a new identity. then, the new node is considered based on the initial solution.
(d) Random route improvement operator
This operator is used to randomly assign the new routes to the nodes until the best possible routes are assigned. Then, based on the initial solution, the new node is revealed as a neighborhood.
(iii) If the stopping criterion is met, the search process stops. Then, the current solution is considered as the best solution.
(iv) Otherwise, the neighborhood revealed by the above said four operators. Then, the neighborhood solutions are checked for Tabu elements. Then, the tabu list is updated by the best solution. Usually, some prescribed number of iterations is fixed as a stopping criterion to obtain the best solution.

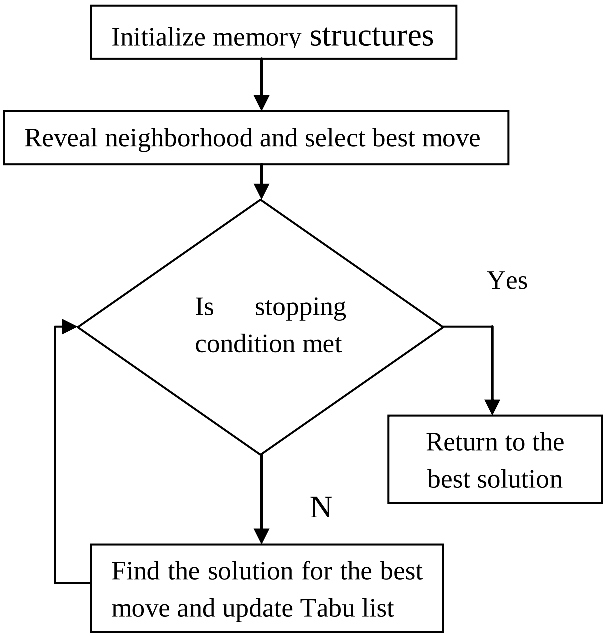



**Figure 6 Tabu search**

## III. PERFORMANCE EVALUATION

In this section, various optimization techniques are analyzed based on their role and performance in the optimal route selection, in the waste management system. The literature survey proved that Ant colony optimization, Genetic algorithm, Particle swarm optimization, and Tabu search, are had a better performance as compared to any other optimization techniques. These optimization techniques were detailed in the previous section.

Mahmuda et al (2015) analyzed the Particle Swarm Optimization (PSO) technique for optimal routing for a solid waste management system with 25 waste bins [36]. The authors optimized the route by considering one depot in the middle of the waste bin network with 3 waste collecting trucks. They concluded that before applying particle swarm optimization the three trucks have to cover 314.88 km to empty the waste bins which are filled with 70% of its total capacity. But, after optimizing the routes by the PSO algorithm, the total distance covered by the three trucks is reduced to 125.35km.in this analysis, they found that 60% of the distance is saved by the PSO algorithm. Eventually, it reduces the overall cost and also the blueprint level of the flue gases.

Serap Ulusam Seckiner et al (2012) proposed an Ant Colony Optimization (ACO) based on the pheromone updation concept [37] and compared the result with the Genetic Algorithm (GA) for ant size 40 and archive size 40. In our case it is considered as several waste bin locations. the authors concluded that their proposed ACO is taken to 20000 epochs with the processing time of 0.2256 seconds. But, for the same parameters, the genetic algorithm reached the target with 2174 epochs with the processing time of 0.0568 seconds.

Shabir Ahmed et al (2020) carried out the performance evaluation between PSO, GA, and BAT algorithms [38]. The authors concluded that BAT had short execution time (20 seconds)that means less number of iterations as compared to other algorithms as PSO execution time 38 seconds and GA execution time 26 seconds.

Milan Misc et al (2017) analyzed a genetic algorithm for optimal routing for a solid waste disposal system [39] with three vehicles for approximately 860.3053 meters length network. In the experimental results. The authors obtained that optimal route with a length of approximately 783.2089 meters in the final stage of the search.

Ingo Von Poser et al (2006) proposed a genetic algorithm [40]with 14 decision variables. the experimental results have shown that The GA algorithm reached its target in 35 seconds. Totally 15 waste bins locations are considered for 15915m length waste collection route network. Nearly 48% of the total distance reduced by the GA algorithm as an optimal route covers the distance 6715m.

Krishna Kumar Mishra et al (2018) analyzed the PSO algorithm [41] and found that it hada poor convergence rate and diversity prevention capacity.

S.R.Agha (2006) proposed mixed integer programming for optimal routing [42] and found that it is reduced to 23.47% of its total length.

Gyanfi et al (2013) proposed sequential ordering for waste collection trucks route by ACO technique [43] and found that the ACO saved 35% of the total cost of the system.

Otoo et al (2012) proposed the ACO method [44] for optimal routing and found that the distance of the waste collection network is reduced into 40% its total length.

Yun yun Niu et al (2018) proposed a hybrid Tabu search [45] for optimal routing for three kinds of networks with nodes 10,20 and 30.they concluded that 18.5 % of total cost saved by this method with the execution time of 1.37s, 1.93s and 2.49 seconds.

Based on the data collected from the above articles. The results are summarized based on the parameters with approximately 40 waste bins locations with 2 or 3 waste collection trucks.

**3.1 The number of iterations:**

In the waste management system, the convergence speed of the optimization techniques or algorithms usually depends on the number of iterations taken by the algorithms to reach the desired optimal routing length for the given network.

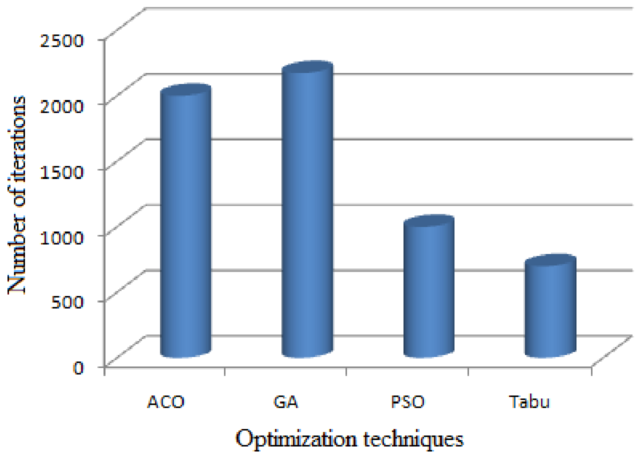



**Figure 7 Optimization techniques Vs Number of iterations**

From the above graph, it is concluded that Tabu search reaching its target with less number of iterations as compared to the other three techniques. On the other hand, GA takes more number of iterations as compared to other techniques.

**3.2 Optimal route length:**

This is the important parameter of the routing system as it decides the efficiency of the optimization techniques for this kind of application. Form the figure 8, it is concluded that PSO is better than other techniques as it reduces the length of the waste collection networkinto almost 60% of its total length.

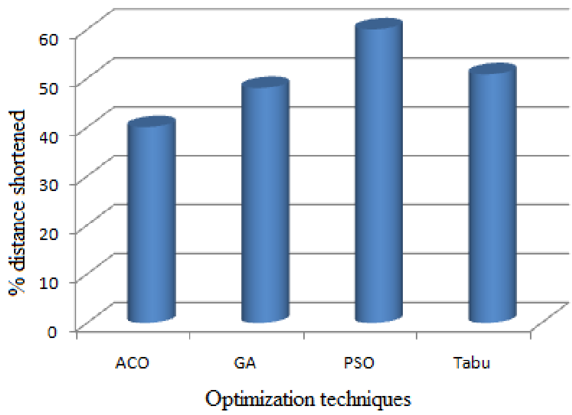



**Figure 8 Optimization techniques Vs % distance shortened**

### 3.3 Execution time:

Usually, for other applications, the execution time depends on the speed of the computing systems. So, it is considered as system dependant. But, in these optimal routing applications, it also depends onthe convergence speed of the optimization techniques.

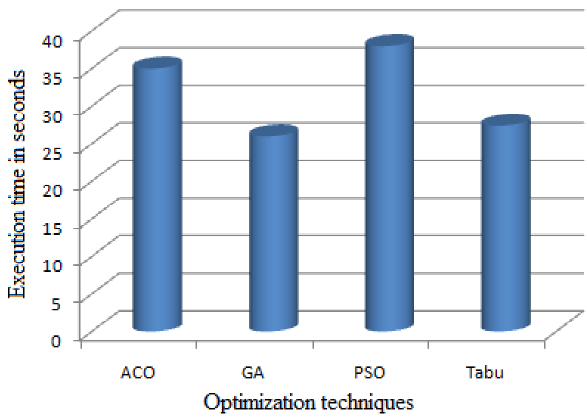



**Figure 9 Optimization techniques Vs Execution time**

From the above graph, it is concluded that GA has a better execution time compared to other techniques.

***Table I:* Performance Comparison between optimization techniques**

| Parameter | ACO | GA | PSO | Tabu search |
|---|---|---|---|---|
| Number of iterations | 2000 | 2174 | 1000 | 700 |
| % of distance shortened | 40 | 48 | 60 | 50.8 |
| Execution time | 35 | 26 | 38 | 27.4 |

The data collected for different parameters of the optimization techniques are summarized in table 1. From the table, it is concluded that the PSO technique yields better performance in optimal routing for the waste collection network, as compared to other techniques. This optimal routing is considered as an important parameter in this application. Because the overall expense of the system is estimated based on this parameter.

But, at the same time, PSO has a larger execution time as compared to other techniques. Because, it has a poor convergence rate and diversity prevention capacity.

By considering all the above parameters. The GA is proved as an efficient one because it has better execution time and optimal route selection capacity.

## IV. CONCLUSION AND RECOMMENDATIONS:

The overall performance of the waste collection optimal routing system is estimated by its cost, total distance covered by waste bins network, the amount of waste collected in each trip, the number of waste collecting trucks, scheduling, routing, and the number of waste bins.

The performance also depends on some other parameters, which impact the system performance indirectly. They are (i) the financial and political decisions of the governments, (ii) poor planning, scheduling, and routing system of the network.

In the above parameters, the distance covered by the waste bins network is considered as an important parameter, because it directly makes an impact on the performance and overall cost of the system.

In this paper, the optimization techniques ACO, GA, PSO, and Tabu searches are reviewed to find the optimal routing for waste management systems. The techniques are briefed neatly with flow chart and procedure with the parameters which are all suitable for this application.

The literature survey shows that only very few articles dealt with the waste management system, by considering its other parameters like (i)nature of the road,(ii)traffic conditions, and (iii) truck scheduling. But, these parameters are also important because they affect the environment and overall performance of the system. especially, for urban areas, where the population is more and roads are maintained poorly.

Based on the reviews, the following points are recommended for further studies and analysis for the researchers.

(i)A holistic approach is needed for optimal routing problems. As the nature of terrain and environments also play a vital role in the performance of the system.

(ii) A 3D model-based analysis is also needed as it improves the efficiency of the system.

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